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Deep Reinforcement Learning based Transmission Policy Enforcement and Multi-Hop Routing in QoS aware LoRa IoT Networks

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Abstract

The LoRa wireless connectivity has become a de facto technology for intelligent critical infrastructures such as transport systems. Achieving high Quality of Service (QoS) in cooperative systems remains a challenging task in LoRa. However, high QoS can be achieved via optimizing the transmission policy parameters such as spreading factor, bandwidth, code rate and carrier frequency. Yet existing approaches have not optimized the complete LoRa parameters. Furthermore, the star of stars topology used by LoRa causes more energy consumption and a low packet reception ratio. Motivated by this, this paper presents transmission policy enforcement and multi-hop routing for QoS-aware LoRa networks (MQ-LoRa). A hybrid cluster root rotated tree topology is constructed in which gateways follow a tree topology and Internet of Things (IoT) nodes follow a cluster topology. A 'membrane' inspired form the cell tissues which form clusters to sharing the correct information. The membrane inspired clustering algorithm is developed to form clusters and an optimal header node is selected using the influence score. Data QoS ranking is implemented for IoT nodes where priority and non-priority information is identified by the new field of LoRa frame structure (QRank). The optimal transmission policy enforcement uses fast deep reinforcement learning called Soft Actor Critic (SAC) that utilizes the environmental parameters including QRank, signal quality and signal-to-interference-plus-noise-ratio. The transmission policy is optimized with respect to the spreading factor, code rate, bandwidth and carrier frequency. Then, a concurrent optimization multi-hop routing algorithm that uses mayfly and shuffled shepherd optimization to rank routes based on the fitness criteria. Finally, a weighted duty cycle is implemented using a multi-weighted sum model to reduce resource wastage and information loss in LoRa IoT networks. Performance evaluation is implemented using a NS3.26 LoRaWAN module. The performance is examined for various metrics such as packet reception ratio, packet rejection ratio, energy consumption, delay and throughput. Experimental results prove that the proposed MQ-LoRa outperforms the well-known LoRa methods.

Keywords: Long Range (LoRa) CommunicationInternet of Things (IoT)Transmission Policy Parameters OptimizationDeep Reinforcement LearningQuality of Service (QoS) ProvisioningMulti-Hop Routing.

1. Introduction

Long Range (LoRa) communication is widely adapted in intelligent transportation systems for monitoring traffic flow, predicting operational issues and car park occupancy, improving passenger experience, etc. [1]. LoRa has many desirable features such as low-power wide-range communication and adaptive parameter support. However, achieving high Quality of Service (QoS) in LoRa communication is still challenging. This is particularly important as LoRa

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technology is frequently used in real-time applications such as intelligent transportation [2], soil monitoring systems [3], fish monitoring systems [4] and disaster response systems [5]. LoRa can be deployed to meet specific application requirements. For instance, cooperative intelligent transportation systems are often characterized by multi-hop communication between roadside units and mobile vehicles that are they are loosely organized with multi-source heterogeneity. In underwater monitoring systems, it is noticed that delay and jitter bounds are necessary to deploy LoRa for real-time systems. In disaster management, increasing in the number of gateways increases the packet delivery ratio. When deployed in high density networks, LoRa suffers slight performance degradations [6]. The analysis shows that optimal transmission policies can assist in achieving better QoS even in large-scale dense networks. For improving coverage and connectivity, multiple gateway deployment is performed [7]. When it comes to QoS improvement, optimal Spreading Factor (SF) allocation is adopted in many research papers. For instance, the Artificial Bee Colony (ABC) algorithm uses Packet Loss Rate (PLR) as the objective function to tune SF and other transmission parameters [8]. The convergence limitations of the ABC algorithm prevent the required QoS provisioning. Furthermore, a Medium Access Control (MAC) protocol is designed by assigning odd/even SFs to the end nodes for enabling concurrent transfer [9]. Poor scalability and large waiting time are the major issues in this work. A game-theoretical approach is presented for assigning SF for end nodes for a particular time period that works upon service requirement [10]. As the work only considers interference, the transmission delay is high for all nodes. Reinforcement Learning (RL) is proposed as the solution for allocating SFs for end devices [11]. Although RL is capable of learning multiple parameters, this work only considers the throughput level, which is inefficient. While the majority of the research focuses on QoS of LoRa, energy efficiency is still a major issue. In general, LoRa uses star topology and single-hop communication, which are the major causes of energy consumption. Thus, SF allocation is performed under the constraint of average energy consumption in LoRa [12]. For optimization, a distributed genetic algorithm, which consumes large time, is utilized. Even with the deployment of edge/fog computing as in [13], the energy efficiency is still an issue. To combat this issue, multi-hop data transmission and optimal topology deployment provide a better solution [14, 15]. Here, it is necessary to select an optimal path to minimize loss rate and energy consumption. Table 1 describes the abbreviations that we have used throughout the paper.

Table 1: List of abbreviations.

Abbreviation	**Expansion**
DRL	Deep Reinforcement Learning
SF	Spreading Factor
BW	bandwidth
CFP	Contention Free Period
MIC	Membrane Inspired Clustering
CR2T2	Cluster Root Rotated Tree Topology
CoMiR	Concurrent Optimization Multi-hop Routing
SSOA	Shuffled Shepherd Optimization Algorithm
MQ-LoRa	Multi-Hop QoS-aware LoRa
MWSM	Multi-Weighted Sum Model
PRR	Packet Reception Ratio

1.1. Motivation

The majority of LoRa communication mechanisms try to optimize QoS in LoRa Internet of Things (IoT) networks. Still, the following restrict the performance of LoRa communication [16, 17].

- Topology – Most of the current research has tested in star or tree topology by considering the gateway as a hub and root, respectively. Both topologies are expensive to construct and have single node failure problems. Maintenance of the topologies also becomes difficult as the network grows in size.
- Routing – Generally, LoRa follows single-hop transmission between an end node and its gateway. In single-hop transmission, energy consumption is high and the coverage is limited to some amount of range, which places restrictions on LoRa's key feature, i.e. long range communication. Current research efforts consider multi-hop routing, but they study limited QoS metrics and solely concentrate on route selection. Routing can offer required QoS when it utilizes full advantage of LoRa including adaptive SF, bandwidth (BW) and Contention Free Period (CFP) factors, since static parameter setting is ineffective in dynamic data transmission cases.

- Data Differentiation – Each data packet generated by end nodes demand a different level of QoS. In such cases, assigning the same priority level leads to improper QoS achievement in the network. For instance, emergency data require low latency and high reliability which must be satisfied by the routing and parameter setting mechanisms. Thus, the absence of priority knowledge is also a cause for QoS degradation.

- Resource Constraint Nodes – IoTnodes are resource constraint in nature. Many LoRa communication techniques fail to minimize the energy consumption of IoTnodes when nodes need to communicate in a single-hop manner. An increase in energy consumption directly degrades the performance of the overall network by decreasing the lifetime of IoTnodes. It is necessary to consider the energy consumption factor of each node in order to achieve an overall QoS level [18, 19, 20, 21].

In this paper, we mainly focus on improving QoS and energy efficiency in LoRa based IoTnetworks. A combined approach that covers topology, parameter and routing optimization is proposed to achieve high QoS in LoRa networks, In Multi-Hop QoS Routing Header Nodes (HNs) collect data from IoT nodes and select optimal multi-hop route with Gateway. Multi-hop transmission is optimized by a multi-Mayfly optimization algorithm and Shuffled Shepherd optimization, both algorithms evaluate the available routes in parallel and rank the routes according to the fitness value. Furthermore to address the energy restriction issue in IoT, in this paper we proposed a scheduling that determines the optimum timeslots for nodes to put in a sleep state. Each node makes decision on sleep time slot by using Multi-Weighted Sum Model (MWSM) that considers multiple criteria such as timeslots selection, buffer status, energy status and event status. Each mechanism introduced in this paper considers both QoS (packet reception ratio, loss rate, latency etc.) and energy efficiency for normal and priority data. The prime objective of this work is to enhance QoS while maintaining energy efficiency in LoRa networks. The sub-objectives are:

1. To optimize the network topology in such a way to support scalability, reliability and energy efficiency.
2. To differentiate the QoS level required by individual messages for providing high network-level QoS.
3. To enable multi-hop routing by considering multiple metrics as per the data type.
4. To assign optimal communication parameters based on the current network status.

1.2. Contribution

In this paper, we provide a holistic solution for cooperative network topology design, resource restriction and transmission policy establishment for LoRa communication through the MQ-LoRa model which consists of the following contributions:

- We present a hybrid network topology namely Cluster Root Rotated Tree Topology (CR2T2). This is constructed using a combination of cluster and tree topologies. This topology avoids the LoRa network single point of failure present in star topologies. All LoRa based end devices use cluster topology and the LoRa gateway devices use tree topology. The root from the end device to its gateway is updated when the congestion level and root score exceed some threshold. Membrane Inspired Clustering (MIC) is performed for cluster formation in IoT. Initially, Signal to Noise Ratio (SNR), distance to gateways, expected emergency data and signal strength are computed for all nodes concurrently. In this way, all gateways in the network use optimal Header Nodes (HNs).

- We propose QRank Extended Frame Structure (QE-Frame) that consists of QoS rank as a new field to identify data into either emergency or non-emergency, where the former requires high level of QoS. For this differentiation, Renyi entropy is used to make the global decision for dynamically adjusting threshold values based on entropy measure. The QRank is further utilized for optimum transmission policy creation and route selection.

- We enforce the optimum transmission policy finding step for both emergency and non-emergency data packets. In LoRa communication, SF, Code Rate (CR), BW and Carrier Frequency (CF) can be optimized. For that, fast Deep Reinforcement Learning (Fast-DRL) is proposed to learn from the environment and accordingly update the QRank, signal quality and SINR. Fast-DRL ensures the required level of QoS with respect to delay and packet reception ratio.

- We design a multi-hop route for satisfying the QoS level of IoTnodes. Two lightweight optimization algorithms are employed for multiple route selection, namely, the Concurrent Optimization Multi-hop Routing (CoMiR) algorithm that runs by Mayfly optimization and the Shuffled Shepherd Optimization Algorithm (SSOA). Both algorithms find the route concurrently and rank the routes through fitness criteria.

- To address the energy restriction issue in IoT, we propose a weighted duty cycle that determines the optimum timeslots for nodes to be put in a sleep state. For accurate timeslots selection, buffer status, energy status and event status were used.

1.3. Layout of this paper

The rest of this paper is structured as follows: Section 2 details the LoRa communication technology and the unique set of parameters. Section 3 briefly discusses the literature in various aspects as LoRa for real-time applications (IoT), transmission policy execution and data transmission. Section 4 gives the problem statement and lists the various research solutions. Section 5 describes the proposed MQ-LoRa in detail that presents the algorithmic steps and working procedure. Section 6 covers the experiment discussion about the proposed and the previous methods using network simulation. Section 7 concludes the paper and outlines future work avenues.

2. PRILIMINARIES OF LoRa

This section summarizes LoRa model operations and communication in detail. A LoRa model consists of a set of end devices, gateways / edge routers, network server and application systems as illustrated in Fig. 1. Devices sense information and forward it to the nearby gateway. The gateway collects all sensed information from devices and sends them to the network servers and they redirect all messages to the application system. A conventional LoRa model consists of two kinds of Open Systems Interconnection (OSI) layers as: (1) Physical Layer, and (2) LoRaWAN MAC layer.

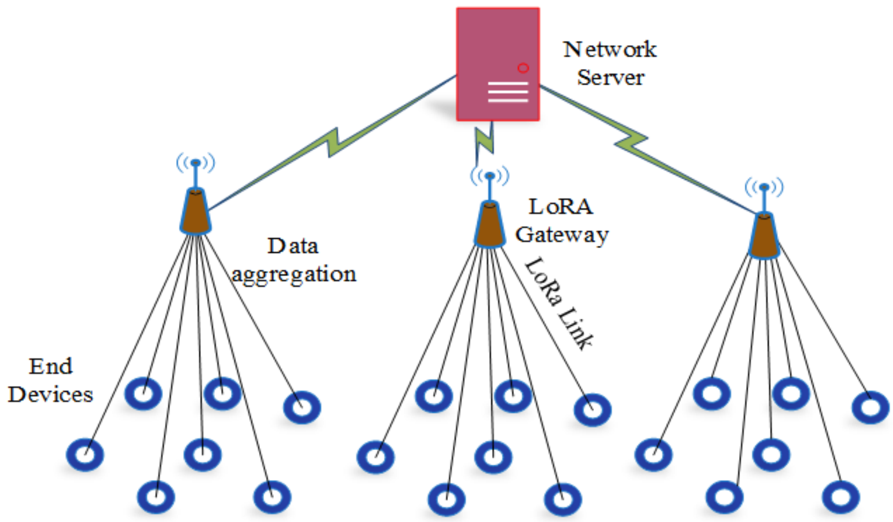

Figure 1: Edge devices in a typical IIoTplatform

One of the major benefits of LoRa is its coverage, where the gateway can cover a long range of end devices. The unique set of LoRa parameters are discussed in table 2.

Table 2: LoRa TECHNICAL PARAMETERS

Parameters	**Standards**	
Spectrum	Unlicensed	
Network Topology	Star	
Communication Range	15 – 16 km	
Type of modulation	CSS	
Peak Data Rate	290 bps – 50 kbps	
Bandwidth	500 – 125 kHz	
Mobility	Better than NB-IoT	
Power efficiency	Ultra large	
Connection density	Utilized with NB-IoT	
Energy efficiency	Greater than 10 years	
Immunity for interference	Ultra large	
Peak Current	32 mA	
Sleep Current	1 μA	
Standardization	De-factor standard	
Spreading Factor	Bit /s	Size (bytes)
12	250(0)	51
11	440(1)	51
10	980(2)	51
9	1760(3)	115
8	3125(4)	222
7	5470(5)	222

The most unified set of features in LoRa technology can be: (i) High coverage with long distance; (ii) low complexity and cost; (iii) long network lifetime; (iv) simultaneous packet receiving option in gateways; and (v) robustness against the Doppler effect. In high coverage, SF12 can be supported to obtain the high packet reception ratio which is greater than 70% over 9 Km. At 5 Km, the value of the packet reception ratio is greater than 70% when the SF is 7. Due to the distance, LoRa parameters such as BW, transmission power, CR and SF must be optimized. For every packet transmission, LoRa consumes 120-150mW and the duty cycle operation consumes less than 0.1% - 10% of power consumption. Thus, the overall network lifetime is sustained from two to five years. LoRa gateways are able to simultaneously transmit packets through 8 channels using different spreading factors such as SF7 to SF12.

3. RELATED WORK

This section is split into three subsections: 3.1. LoRa for real-time IoT applications. 3.2. Transmission policy execution and 3.3. Data transmission.

3.1. LoRa for Real-Time IoT Applications

LoRa communication is widely used in long-range communication. In[22], Dynamic Line Rating (DLR) for overhead transmission line (OTL) is proposed to monitor the temperature, this application depends on predisposition measurements, weather, and temperature. This method uses the vision system that transmitted by LoRa and communication is conducted between Supervisory Control, Vision system, And Data Acquisition (SCADA) system. This study highlights that QoS plays a major role in the reliability of received data. Besides the IoT and industrial IoT applications [23], LoRa is also useful in disaster management and emergency response systems. This paper designs LoRa based communication for such systems. The proposed LOCATE system, which is a phone-based emergency communication service is utilized to enable long-range communication in the absence of 4G/5G cellular links. To cope with emergency communications, LoRa uses a multi-hop dissemination mechanism in Emergency Communication Systems (ECS) s. The primary objective of this dissemination is to maximize the probability of delivering emergency data. In other research [24], LoRa communication is applied in soil monitoring applications. This paper proposes a Radio Frequency Identifier (RFID) sensor based LoRa communication. Multiple RFID sensors with energy harvesting capability are deployed in the environment. The LoRa block is responsible for collecting data from the RFID sensors. Then, the collected data is processed to find the quality of soil in the farmlands. LoRa communication is employed for underwater monitoring [25], namely Internet of Fish (IoF). The LoRa addon module is integrated with the acoustic transceivers to enable LoRa radio support for underwater systems. The system is tested in real-time and the delay is highlighted as a main limitation of LoRa since it does not provide any delay or jitter bounds. Often, real-time monitoring systems always demand data transmission without any delay because they need to detect events in a timely manner. A disaster response system is presented in [26] based on LoRa communication. Mainly, LoRa is used for citizens to report their emergency data to the central authorities in case of broken cellular links. This paper allows multiple gateways in the network in order to meet the required level of data delivery rate and successful packet delivery ratio. With an increase in the number of gateways the packet delivery ratio is increased up to 95% which is relatively greater than that of the network with a single gateway.

3.2. *Transmission Policy Execution*

In [27], the authors demonstrate that the focus on optimal transmission policies can improve the performance of data transmission systems including SF allocation, many factors are affected by SF allocation including the distance to the gateway. It is impossible to ensure better data transmission efficiency with single gateway in large network size. In this study, a smart city application of an IoTsetting is deployed with a high node density network to address the scalability challenge of the LoRa technology. Data transmission capability of the system was negatively affected when the network scale is increased. To overcome transmission policy related limitations, the LoRa technology uses a Received Signal Strength Indicator (RSSI) [28]. Multiple gateways are deployed in this method because the system is designed for coastal applications, [26] gets the satisfactory level of connectivity and coverage in the network with multiple gateways. RSSI is considered for SF allocation and the data is encrypted for security reasons. Optimal SF allocation is studied in [29] to achieve better communication performance. The target of this work is to minimize the interference introduced due to the allocation of same SF for multiple nodes to transmit to a single gateway. Thus, each node is assigned with a particular SF for a fixed time. This time is estimated in an optimal manner based on the service requirement of the node. A game theoretical approach is proposed to manage interactions among the IoTnodes. The SF allocation considers the interference factor only which is insufficient for IoTnetworks. Although LoRa communication is more energy efficient that IoTradio technologies, energy consumption is still one of its major limitations due to the single-hop transmission between a node and its gateway. To address this issue, the authors of [30] propose an energy-efficient SF allocation policy. The problem of SF allocation is formulated as an optimization problem and it is resolved under constraint of average energy consumption while maximizing packet reception ratio. For optimization, a distributed genetic algorithm is proposed to assign optimal communication parameters for each node in the network.

3.3. *LoRa based Data Transmission*

In [31], a MAC protocol for the LoRa technology is proposed. The proposed protocol relies on the capture effect among the signals with same SF and performs an odd/even based SF allocation for demodulation. In order to transmit data simultaneously, the SF first checks whether it is odd or even. If odd, then the odd slot is assigned in the case that slot is free. Otherwise, the odd SF signal must wait until the next odd slot for transmission. This work introduces high waiting time which further increases the transmission delay. In [32], the authors present a LoRa-REP access method for minimizing the average transmission time and maximizing success probability through a message replication mechanism. Mainly, this work focuses on emergency data transmission. For that, two operational infrastructures, namely, LoRa with cloud backend and LoRa with local (edge/fog) backend are constructed. The success probability is set up in the completion of the confirmed data exchanges in emergency management. Although the waiting time is minimized, the energy consumption is still relatively high. A multi-hop communication scheme is presented in [33] for LoRa based sensor network. In this work, it is shown that the traditional star topology is not suitable for large-scale implementation of LoRa communication. Thus, a linear sensor network topology is proposed with multi-hop data transmission strategy. The linear sensor network topology resembles a hierarchical point of view. The hierarchical nodes are arranged as basic sensor nodes, data relay nodes and data dissemination nodes. The multi-hop routing is performed through relay and dissemination nodes. Although multi-hop data transmission minimizes energy consumption, involvement of non-optimal wake-up scheduling increases energy consumption. Parameter tuning is a significant task in LoRa which is discussed in [34] and [35]. In [34], an optimization approach is presented for LoRa parameter optimization. The paper aims to achieve minimum Packet Loss Rate (PLR). The proposed optimization works upon the ABC algorithm. The gateway LoRa network monitor (GLNM) is able to monitor real-time traffic in order to configure the required parameters. Here, the ABC algorithm is implemented to tune the LoRa parameters such as SF, CR and BW in an optimal manner. The ABC algorithm has some convergence issues which affects the optimal parameter tuning process. Similarly, in [35] a machine learning approach is presented for updating parameters in LoRa networks. The objective function is formulated as the function of throughput maximization. At first, an average throughput attained by a node is mathematically formulated. Then, the network level configuration is derived optimally. For parameter updating, a reinforcement learning approach is proposed that works upon the throughput factor. Data transmission is performed on the basis of policies derived by reinforcement learning. A Real-Time LoRa (RT-LoRa) communication protocol is presented in [36] for industrial IoT applications. The RT-LoRa uses a medium access strategy to process the real-time flow. The overall network is constructed with mobile nodes and static nodes. For all static nodes, the QoS level is considered to be the same. For flows generated by mobile nodes, the QoS level is divided into three classes such as normal, reliable and most reliable. In accordance with the QoS level, the strategy allocates SF and CF. The static and mobile nodes are arranged and communicated with the gateway in a star topology. The significant issues presented in this paper are follows: The overall procedure is presented for a single gateway network through single-hop communication. This causes large transmission delay, up to 28s, for most reliable flows even within 180 meters. In real-time, industrial data requires more coverage and lower time delay which has not been addressed in this work. The QoS level is assigned for mobile nodes only and all static node flows are assigned with the same priority level which introduces restrictions in QoS provisioning. The star topology of nodes is not suitable for large-scale networks and introduces a single point of failure. Energy consumption is also high for all nodes to communicate with the central gateway and it is even higher for nodes that are further away from the gateway. A LoRa+ protocol is presented in [37] to improve QoS in terms of rejected packet rate reduction and packet error rate reduction. The problem addressed by this paper is the current assignment of SF and operational frequency which is used for next uplink transmission too. In LoRa+, the two parameters are updated for class "A" end devices in order to minimize the waiting time for next slots and to minimize the rejected packet rate. To achieve this aim, a new frame structure called "Configuration Frame" has been designed with Expected Time of Arrival (ETA) information. SF allocation is performed based on a RSSI. This paper has the following shortcomings: A single metric RSSI is considered for SF allocation which is insufficient since some packets need low latency which is not satisfied by considering the RSSI metric alone. This is because, the RSSI based allocation only focuses on the reliability and the latency requirements are not considered. LoRa+ also follows the same SF and CF in case of high RSSI of received data. This leads to higher energy consumption and data loss. Scalability of the work is poor since it is only suitable for medium scale networks such as in rural areas. To improve QoS in LoRa, researchers in [38] first derive the mathematical model of an IoT node. The closed form formula is derived to formulating the node performance. For articulating node's performance, a Markov chain model is utilized, and performance is increased by optimizing the performance of IoT nodes. Then, the optimal transmission policy is derived on the basis of the mathematical model. The transmission policy is defined in terms of SF and CF factors. This work considers normal and emergency data, performance is optimized by assigning optimal SD and CF factors using a Simulated Annealing (SA) and Genetic Algorithm (GA). Data require different levels of QoS that is not attained in this work, the fitness function is formulated for normal and emergency data and parameters are updated by GA and SA. Optimal parameter assignment for packets by GA and SA is comparatively difficult, because to handle scalable problems with GA is not easy and SA is slow and sensitive to changes in the input values. Furthermore, it has the following limitations: This work aims to improve energy efficiency by taking it as constraint in fitness evaluation. In LoRa, reliable communication can be achieved only in the cost of energy consumption since it uses single hop transmission. Involvement of single-hop communication increases energy consumption and is ineffective for large-scale networks. A QoS provisioning approach is proposed in [39] through fine tuning of radio parameters such as SF and CF. The problem of QoS provisioning is formulated as Mixed Integer Linear Programming (MILP). Then, optimal setting of SF and CF is determined under the constraint of data extraction rate (DER) to reduce the packet collision rate. The SF is decreased based on SNR of the received frames as the function of SNR needed for demodulation. Furthermore, the problem is resolved by adopting a CPLEX optimizer and approximation algorithm. This work suffers from the following issues: It is only suitable for short range communication in small-scale network in which a single gateway is used. But the main motive of LoRa is long rage communication. This work affects the long range communication for achieving QoS. The approximation algorithms are difficult to run and the high complexity implies it is unsuitable for large-scale inputs. As the approximation algorithm is complex and all transmission is carried by single-hop, energy consumption is relatively high in this work. A real-time monitoring application based on LoRa communication is presented in [40]. The proposed approach is built upon a multi-sensor fusion model with multi-hop data transmission. In this work, the sensors are deployed in the wetland and the collected data is transmitted to a remote server through a Base Station (BS). Further analysis takes place via a fuzzy decision-making based data fusion approach. For data collection, a queue-based data upload scheme is introduced. A threshold based sleep scheduling is enabled for sensors to minimize energy consumption. This work has the following limitations: Sleep scheduling is performed based on the threshold value, i.e., if a node collects the same data which is lower than threshold level for 10 times, then that node enters the sleep state for 60 mins. In monitoring applications, it is unsure that there will be no events taken place for 60 mins which affects the reliability. As the sleep decision is taken by each node without knowledge on other nodes, it is possible for all nodes to be in sleep state. For timely analysis on the state of the application, the emergency data must be transmitted without any waiting time or delay. Here, the BS decides which data is collected at this time instance in queue model which is unaware of the emergency level of data the device hold. To mitigate the issues in single-hop routing in LoRa, in [41], the authors propose a multi-hop routing algorithm. In this simplified version of destination-sequenced distance vector routing protocol, the QoS is measured as the function of Packet Reception Ratio (PRR) and throughput. Here, the network comprises sensor nodes, relay nodes and a gateway. The gateway rooted tree topology is constructed in which sensors act as leaf nodes. The leaf node transmits the data to nearby relay node which is responsible for executing a routing protocol and to select a route with gateway. When the packet arrival rate is high, then PRR is relatively low in this work since the relay nodes have to find route for each packet. This is because the distance vector routing generally consumes more time which prevents the relay nodes from meeting a deadline of such packets which affects reception ratio. This work requires relay nodes to assist data routing. For large-scale networks, a larger number of RNs is required which increases deployment cost. The route selection only considers number of hops which is insufficient for achieving better performance since the data transmission is affected by other factors such as noise level, channel quality and so on. Single gateway is set as root and all other nodes are considered to be leaf node. Maintaining this large tree structure is difficult and complex. In addition to this, if the root node is affected then the overall data transmission will be affected. As LoRa generates a huge data demand, a different level of QoS. In such cases, assigning the same priority level leads to improper QoS achievement in the network. For instance, emergency data require low latency, high capability and reliability, which could not accurate enough be satisfied by the previous works as shown in table 3. Furthermore, LoRa technology frequently depends on a star topology. Most of the current research has tested in star or tree topology. Both topologies are expensive to construct and have single node failure problems. Maintenance of the topology also becomes difficult in such a way to support scalability, reliability, and energy efficiency of LoRa.

Table 3: Summarize the contribution of state the approach and result achieved by other research in the literature.

Existing Work	**Problems Addressed**	**Proposed Solutions**
[36]	- The overall procedure is presented for a single gateway network through single-hop communication. This consumes large transmission delay up to 28s for most reliable flows even within 180 meters. - The QoS level is assigned for mobile nodes only and all static node flows are assigned with same priority level which introduces restrictions in QoS provisioning.	- The proposed network model is constructed with multiple-gateway based cluster architecture along with multi-hop communication to minimize energy consumption. - Rotated-tree topology is proposed for gateways and cluster topology is proposed for IoT nodes which improves the performance of the network.
[37]	- LoRa+ follows the same SF and CF in case of high RSSI of received data. This leads to higher energy consumption and data loss. - Scalability of the work is poor since it is only suitable for medium scale networks such as in rural areas.	- Consideration of QRank allows providing required level of QoS for all packets. - Proposed CR2T2 topology supports large-scale networks by forming multiple clusters

[38]	- The parameters are updated by GA and SA. GA is complex in nature and difficult to handle scalable problems. - This work aims to improve energy efficiency by taking it as constraint in fitness evaluation. Involvement of single-hop communication increases energy consumption and ineffective for large-scale networks.	- Proposed CoMiR algorithm (uses Mayfly and Shuffled Shepherd optimization algorithm) computes different fitness values for routes upon QRank. - Parameters are updated by Fast DRL which is fast and efficient since it learns the environment continuously.
[39]	- This work is only suitable for short range communication with small-scale network in which probably single gateway is used. - The approximation algorithms are difficult to run and high complexity mainly it does not suitable for large-scale inputs.	- Multi-gateway architecture is proposed with novel CR2T2 topology that enhances coverage and scalability. - Proposed Fast DRL is capable of processing multiple inputs at a time.
[40]	- Here, sleep scheduling is performed based on the threshold value (i.e.) if a node collects same data which is lower than threshold level for 10 times, then that node enters the sleep state for 60 mins. In monitoring applications, it is not sure that there will be no events taken place for $60mins$ which affects the reliability.	- MWSM based dynamic sleep scheduling is proposed for IoT nodes under the constraints of Buffer Status, Energy Status and Event Status. - The data transmission is performed based on QRank which is determined by emergency level of data
[41]	- This work requires relay nodes to assist data routing. For large-scale networks, more number of RNs are required which increases deployment cost.	- HN finds optimal route by CoMiR optimizer which can handle large number of packets. - Root-rotated multi-gateway architecture is proposed for handl in large-scale network

4. Solutions Outline

This section describes the research solutions for addressing the problems illustrated in the literature work. In this paper, a network model with multiple-gateway based cluster architecture along with multi-hop communication is assumed. All nodes rank the packets according to QoS level in the QoS-extended frame structure which is further utilized in routing and parameter update stages. We propose a CR2T2, a rotated-tree topology, for gateways and a cluster topology for IoT nodes to improve the performance of the network and to minimize energy consumption. Fast DRL considers multiple important metrics (QRank, SINR, and SQ) for SF and CF allocation. Consideration of QRank provides a required level of QoS for all packets. In this paper, CR2T2 topology supports large-scale networks by forming multiple clusters. HN finds optimal route by CoMiR optimizer which can handle large number of packets. Route selection considers multiple parameters based on QRank. The proposed CoMiR algorithm, which uses Mayfly and SSOA, computes different fitness values for routes upon QRank. Parameters are updated by Fast DRL which is fast and efficient since it learns the environment continuously. Multi-hop transmission is optimized by a multi-Mayfly optimization algorithm. The Multi-Weighted Sum Model (MWSM)-based dynamic sleep scheduling is proposed which considers the buffer status, energy status and event status parameters. The data transmission is performed based on QRank which is determined by the emergency level of data. Based on the research solutions described above, we address each problem in turn. In subsequent sections, the detailed procedure of every research solution is given.

5. MQ-LoRa Model

The proposed MQ-LoRa is segregated into five related steps: (1) hybrid topology construction; (2) data QoS ranking; (3) optimal transmission policy enforcement; (4) multi-hop QoS ranking; and (5) weighted sleep scheduling.

5.1. Network Architecture

In this research, a novel Multi-Hop QoS-aware LoRa (MQ-LoRa) is proposed for achieving better QoS and energy efficiency for IoT networks. MQ-LoRa comprises IoT nodes (end devices), multiple gateways, network server and a cloud server. The objective of MQ-LoRa is to optimize the transmission policy parameters of the LoRa network to maximize the network reliability $\mathfrak{R}$, say. In general, a LoRa network is configured by four sets of parameters (defined as SF= δ_f, CR= $C\gamma$, BW= bw and CF= C_{fr}) that influence the packet delivery ratio and network reliability. Hence, these factors are used to define the constraints of the problem. Fig.2 represents the system model when $\delta_f = \{7, 8, 9, 10, 11, 12\}$, $bw = \{125, 250, 500\}$ and $C\gamma = \left\{\frac{4}{5}, \frac{4}{6}, \frac{4}{7}, \frac{4}{8}\right\}$. The optimization function is utilized to achieve maximum reliability in both emergency and non-emergency packet transmissions, which is formulated as,

$$OF_{N(i)} = Max\mathfrak{R}; \left[\delta f\ (i)\ ,\ C_{\gamma}\ \ (i)\ ,\ bw\ \ (i)\right] \tag{1}$$

The received power of each LoRa gateway can be represented by follows:

$$P_{RX(i)} = P_{TX(i)} - l_i \tag{2}$$

where $P_{TX(i)}$ represents the transmission power of i the device and l_i is the path loss between the gateway and i. Similarly, $SINR_{i,j}$ is computed for the desired LoRa signal to decode which is computed by,

$$SINR_{ij} = \frac{P_i}{P_j + \sigma^2} \geqslant Q_{ij} \tag{3}$$

where p_i and p_j, i and j values are different from 7, 8, 9, 10, 11, and 12 are the power of the desired and interfered symbol, correspondingly, σ^2 is the channel noise power, and Q_{ij} is the threshold value which is often from 6 dB to 7 dB. A novel topology is introduced to replace the conventional topology. The major methodologies involved in MQ-LoRa are discussed below.

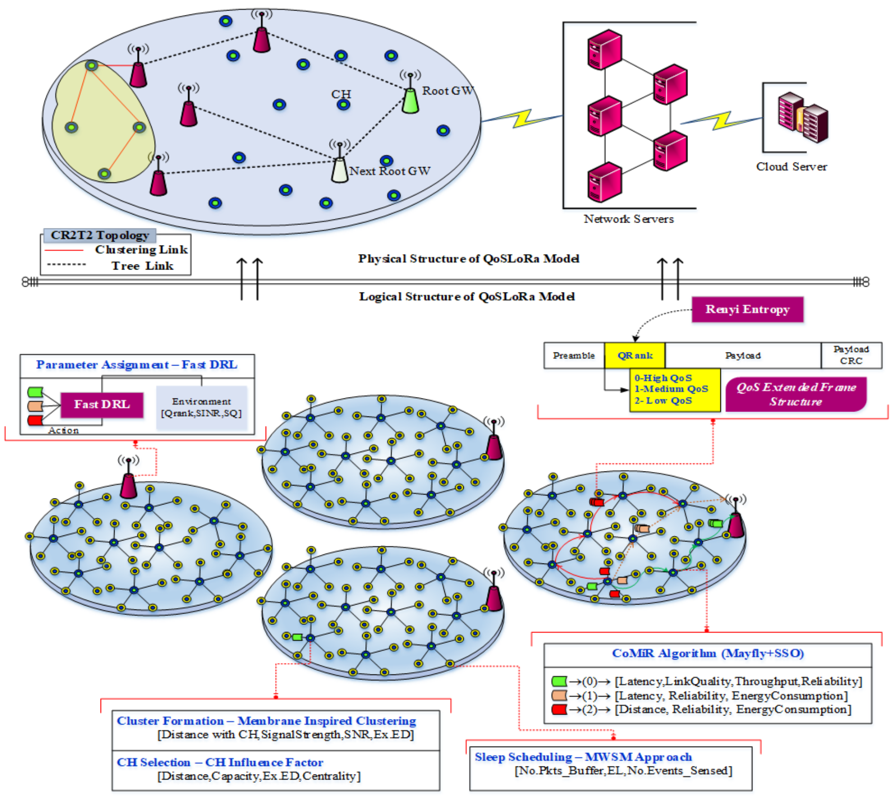

Figure 2: The system model

5.2. Hybrid Topology Construction

The initial network construction implements a novel hybrid topology CR2T2 which is constructed by combining cluster and tree topologies. The gateways form a tree topology while the underlying IoT nodes form a cluster topology.

In the tree topology, regular root rotation is performed based on the congestion level and root score. The root score represents the number of times that particular gateway serves as the root node.

Cluster formation among IoT nodes is carried by the MIC algorithm [42, 43, 44]. MIC is parallel computing algorithm, which derive from inspiration of the procedures that take place in the biological cell. These systems subsist of various regions in the shape of certain architectures. MIC is a biological process that is often known as p systems. The proposed MIC is a new algorithm that effectively addresses the clustering problems. The procedure of MIC is the inheritance of a biological cell, i.e., MQ-LoRa uses a cell like structure for clustering similar sets of devices. The main objective of MIC is to group the devices into k numbers of clusters according to the similarity criteria, e.g., residual energy. For that reason, MIC uses two kinds of rules as evolutionary and communication rules. The evolutionary rule is computed by configuration change and its principle of evolutionary algorithm (particle swarm optimization) and the traditional MIC uses genetic programming (GP), but GP does not address time complexity and space complexity issues. Hence, Particle Swarm Optimization (PSO) is taken into account for evolutionary communication [45]. Here, object / data point is denoted as the IoT device. Assume that each device i in every cell J can be evolved in the following way:

$$E_j^i = E_j^i + wE_j^i + c_1 r_1 (P_j^i - E_j^i) + c_2 r_2 (l_j^i - E_j^i) + c_3 r_3 (q_j^i - E_j^i) + c_4 r_4 (q_j^i - E_j^i) \quad (4)$$

where c_1 , c_2, c_3 and c_4 are the input parameters which are distance with gateway, capacity, centrality and expected emergency data, respectively. The parameters r_1, r_2, r_3 and r_4 are the random real numbers which range from 0 and 1. The value of w is computed in terms of the min and max for each input parameter for cluster formation and the number of steps is defined in t_{max}. The value can be computed for t step is illustrated below:

$$W = W_{max} - \frac{t(w_{max} - w_{min})}{t_{max}} \quad (5)$$

Finally, P_j^i, l^i, q^i and u^i indicate the best position of device E_j^i, local best device in cell i, external best device, and global best device, respectively. Each best device can be randomly computed and selected from all over the cells by communication rules. To update the best position of each device, we use the behavior of PSO. Each IoTnode N_i(i=1…n) in network computes the distance between two nodes by Euclidean Distance, i.e., dz is computed by follows,

$$dz = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2} \quad (6)$$

where $(x_j - x_i)$ and $(y_j - y_i)$ represents the coordinates of node i and j. The distance between i and j for all other devices in network is expressed by a matrix and the representation is follows:

$$dz = \begin{bmatrix} 0 & dz_{1,2} & dz_{1,n} \\ \ldots & \ldots & \ldots \\ dz_{n,1} & dz_{n,2} & 0 \end{bmatrix} \quad (7)$$

Among all devices in the network, the centroid value c_γ is computed between network pairs and the formulation is follows

$$c_\gamma\left(\left(x_i - x_J \right)\left(x_i - y_j \right)\right) = \left(\frac{x_i + x_j}{2}, \frac{y_i + y_j}{2}\right) \quad (8)$$

The first device coordination is referred to as the centroid point. According to the dz and c_γ, a new centroid value is computed. When c_γ falls within the dz, then that node is chosen for the same cluster. Otherwise, it is connected with another cluster that have a similar dz value. The cluster type prediction is given below:

$$S_{C_{(i)}} = \begin{Bmatrix} Same\ C_{(i)}, if (C\gamma \pm dz) \\ Distinct\ C_{(i)}, Otherwise \end{Bmatrix} \quad (9)$$

Therefore, the sum of clusters generated by the MIC is calculated as follows,

$$\varsigma = \sum\nolimits_{k=1}^{n} count(c_\gamma) \quad (10)$$

For ς the standard deviation is computed which is denoted as D_ς that computed by

$$D_\varsigma = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n} dz^2(x_i, x_j)} \quad (11)$$

where n is the number of nodes in the network. The smaller the value of D_ς indicates the best outcome in the network. The procedure for cluster formation is represented in Fig. 3.

After the cluster formation, the corresponding gateway selects optimal HNs based on Influence Score fs and this value is determined using SNR and distance with neighbor nodes D_N , Energy Status ε_δ , Expected Emergency Data ε_{ed} , and Received Signal Strength (RSS).

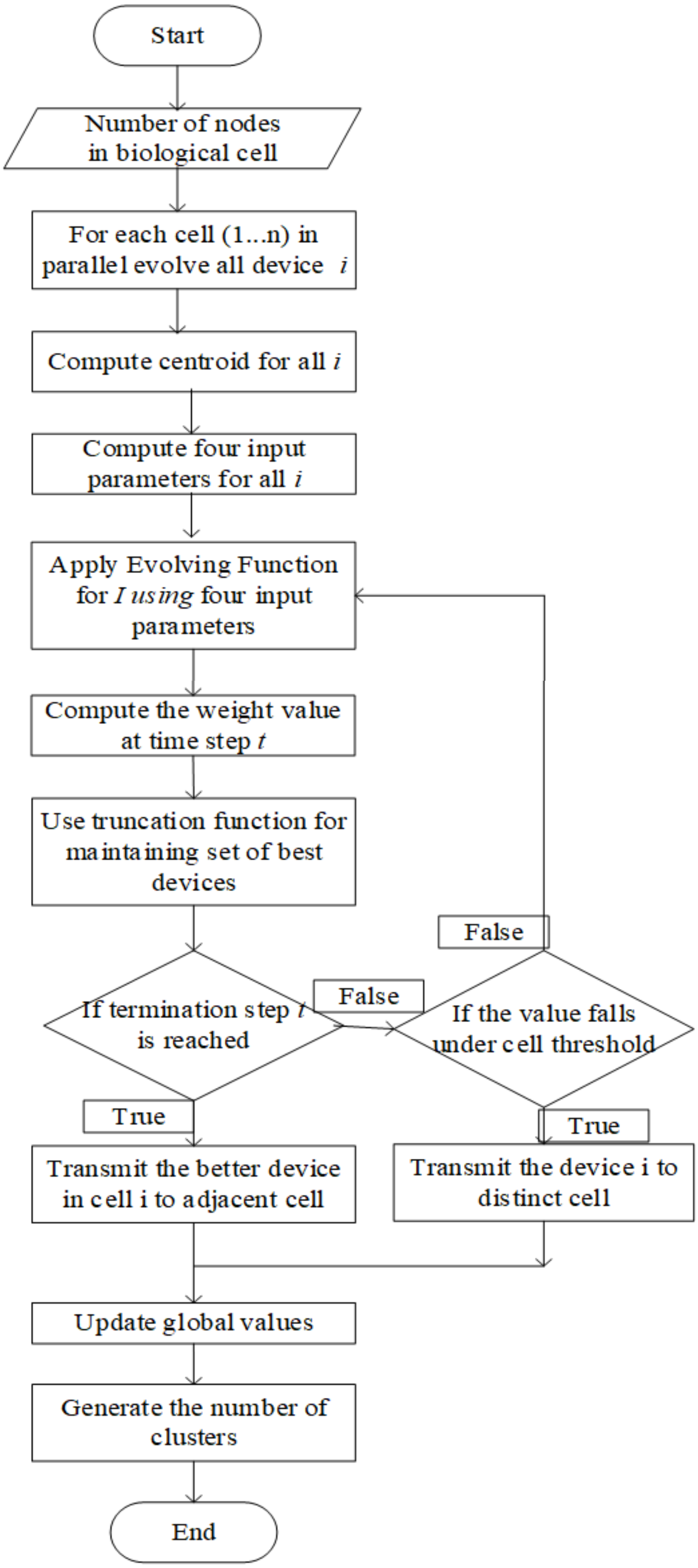

Figure 3: Flowchart for cluster formation

RSS is computed for the node which is based on the power occupied in the radio signal obtained from gateway GT. It is expressed as follows,

$$RSSI = P_0 \left(\frac{dis\,(N_i, GT)}{dis_0} \right)^{\sigma} \tag{12}$$

where P_0 is the reference power received at the position of distance dis_0 and σ represents the path loss component.

All these parameters are essential in HN selection. For instance, the IoT device energy is split into three processes as sense, transmit and receive. The HN must perform one more action, i.e., collection and aggregation. When a node energy is depleted, packet transmission is lost and also frequent HN election is introduced. Therefore, we consider all significant metrics of a device to prefer the stable HN.

Objective Function for HN Selection: This function helps to determine the optimum HN among the multiple nodes in the cluster. This objective function OF computation can be formulated as follows:

$$OF_i = w_1 \times SNR(i) + w_2 \times D_N(i) + w_3 \times \varepsilon_\delta(i) + w_4 \times \varepsilon_{ed}(i) + w_5 \times D_N(i) \tag{13}$$

where w_1 , w_2 , w_3 , w_4 and w_5 are the weight parameters for each input parameter taken for HN election. The proposed MQ-LoRa can elect the best HNs when the weight values are 0.25 for all weight variables. On the basis of cumulative parameters, HN selection and cluster formation is performed. The proposed CR2T2 topology is scalable and also energy efficient for handling any number of nodes in network. In MQ-LoRa, MIC based cluster formation and HN election produces the O(C×D×n) where C, D and n represents the number of clusters, dimensions of each node to be clustered and the number of nodes in the cluster.

5.3. Data QoS Ranking

Once clusters are formed, the data transmission is carried between IoT nodes and gateways through elected HNs. Each IoT node is responsible to determine the QoS Rank (QRank) of the data. In general, the IoT nodes have normal data and emergency data upon varying time constraints. A data transmission scheme must satisfy the QoS level required by normal and emergency data. Table 4 shows the three levels of QRank for QoS provisioning.

Table 4: QRANK ANALYSIS

QRank	**Description**
RANK_0	Emergency Data
	Requires High Level QoS
RANK_1	Normal Data
	Requires Medium Level QoS
RANK_2	Periodic Data
	Requires Base Level QoS

The data collected by an IoT node is differentiated into emergency and normal based on the Renyi Entropy that determines the threshold value. The decision threshold is dynamically changed based on the entropy measure. The QRank is appended in the QoS-Extended Frame Structure (QE-Frame) of LoRa. The QRank is further utilized in route selection and parameter allocation. Fig. 4 represents the LoRa frame structure in which QRank is modified and newly added in the frame structure. A QRank analysis is illustrated in Table 4.

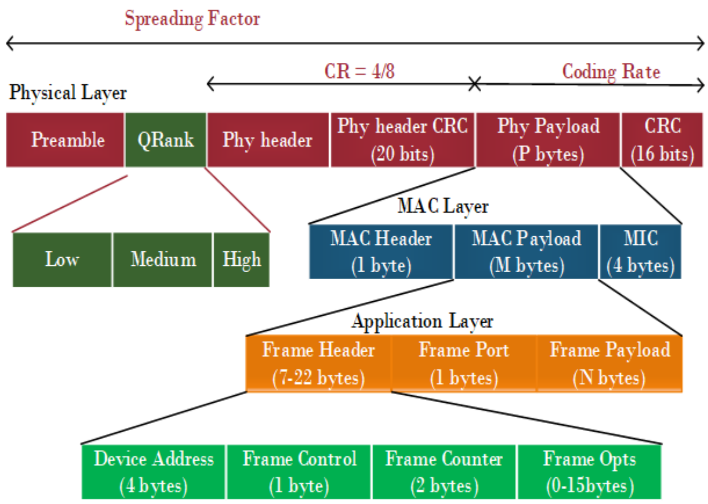

Figure 4: LoRa frame structure

5.4. Optimal Transmission Policy Enforcement

For all data, it is necessary to allocate optimal parameters (SF, C_γ, BW, CF) to achieve the desired QoS. Each parameter is described as follows: SF is the most significant parameter for LoRa communication. When SF decreases, then energy consumption and time of air values also decreases gradually, then the network throughput is maximized, but this is a hindering task if coverage is longer. The mathematical formulation of the SF is expressed by follows:

$$SF = log_2 \frac{C_p}{\delta_\gamma} \tag{14}$$

where C_p represents the chip rate and δ_γ represents the symbol rate. LoRa communication parameters are identified by data rate R_b which is calculated by,

$$R_b = SF \times \frac{bw}{2^{SF}} \times C_\gamma \tag{15}$$

Where c_γ is the Coding Rate, bw range from 125, 250, or 500 kHZ, SF is the spreading factor that range from 7 to 12, c_γ is range in between 4/5 to 4/8. These values are shared between the transmitter and receiver for modulation and demodulation. Other significant metric is defined by the following:

$$S = -174 + 10 \times log_{10}(bw) + nf + SNR \ [dBm] \tag{16}$$

where S the receiver sensitivity, nf represents the receiver noise figure, SNR denotes the SNR, and -174 is the thermal noise that range is by 1 Hz. The c_γ ranges from 1 to 4 and to maximize the resilience for corrupted bits, LoRa support forward error correction technique with variable number of c_γ of redundant bits that range from 1 to 4. The code for LoRa is computed by

$$C_\gamma = \frac{4}{4+n} \ with \ n \in \{1, 2, 3, 4\} \tag{17}$$

LoRa radios consist of 4/5 to 4/8 of c_γ used in payload. If the c_γ is higher, then packet reception rate is higher. The bw is computed for the different range of frequencies over LoRa chirp spread allows for trading radio airtime against radio sensitivity.

LoRa protocol consists of 125 to 500 kHz, but the higher BW utilization result packet transmission in higher data rates. The CF is the number of LoRa transceivers use sub-GHz frequencies for data transmission. Some of the CFs to communicate using LoRa are 433 MHz, 868 MHz, 915 MHz. We propose a novel Fast-DRL named Soft Actor Critc (SAC) for optimal transmission policy enforcement. SAC, learns the environmental parameters such as [QRank, Signal Quality, SINR] to allocate optimal transmission policy as State S_{ta}, Action A_{ct} and Reward R_{ew}. The optimal transmission policy is determined by the A_{ct}/S_{ta}, where determines the policy made by A_{ct} and S_{ta} of the data parameters. All data in the network are necessary to allocate the parameters which include C, bw and CF. The SAC in the gateway learns the environment that contains the data parameters and take action, reward according to it, the equation for giving S_{ta}, A_{ct} and R_{ew} are given below,

$$A_{ct} \sim (A_{ct}/S_{ta}) \tag{18}$$

$$S_{ta+1} \sim \Pr ob\ (S_{ta+1}/A_{ct}, S_{ta}) \tag{19}$$

$$R_{ew} \leftarrow (A_{ct}, S_{ta}, R_{ew}(A_{ct}, S_{ta}), S_{ta+1}) \tag{20}$$

Above equation represents the S_{ta}, A_{ct} and R_{ew} for the allocated data parameters in the LoRa environment. Initially path of action and state of action is to find an optimum transmission policy that is given in eqn (18), then probability is find for the unknown state based on the previous state and action which given in eqn (19) and reward is given based on the action of the allocated parameters such as less SF, high C, high bw and CF. As QRank is considered in SAC, required level of QoS is ensured in terms of PRR and delay.

5.5. Multi-Hop QoS Routing

HNs collect data from IoT nodes and select optimal multi-hop route with Gateway. Multi-hop route selection is performed based on the QRank of packets. The problem multi-hop route selection is formulated as optimization problem, we propose novel Concurrent Optimization Multi-Hop Routing (CoMiR) algorithm that works on the procedure of two new optimization algorithms such as Mayfly Optimization and Shuffled Shepherd Optimization. The mayfly algorithm is a Bio-inspired algorithm from the mayflies which is fit to the insect order called ephemeropetra. The best male and female selection for mating process was handled by the mayflies optimally based on the fitness values. The proposed work chooses mayfly optimization algorithm for finding the best route based in the LoRa networks on the fitness value. The shuffled shepherd algorithm is also a Bio-inspired algorithm form the shepherd behavior that how to guide the herds to correct path. Both algorithms evaluate the available routes in parallel and rank the routes according to the fitness value. As we consider three levels of QRank, three different fitness functions are formulated for each rank. The fitness criteria are given in Table 5. The formulation explanation of the Mayfly and SSOA are given below,

$$R_{ou}(1) = R_{ou}(0)_{Lat,rel,LQ,TP} + R_{ou}(0) \tag{21}$$

where $R_{ou}(0)$ is the first route that wishes to change its position to the second route $R_{ou}(1)$ with awareness of first route $R_{ou}(0)_{Lat,rel,LQ,TP}$ latency, reliability, link quality and throughput, similarly for third route that can be formulated as,

$$R_{ou}(2) = R_{ou}(1)_{Lat,rel,LQ,TP} + R_{ou}(1) \tag{22}$$

The equation for finding the best route path can be formulated as,

$$N = N_0 - \frac{N_0}{\max search} \times search \tag{23}$$

$$\Re = N_0 - \frac{N_{\max} - N_0}{\max search} \times search \tag{24}$$

The above equation (23) represents the selection of the best first route path $R_{ou}(1)$ and equation (24) represents the selection of worst route path $R_{ou}(n)$. The decrease in N and increase in $\Re$ that gradually increase the effectiveness of the optimize route selection in the LoRa networks. Finally fitness value is calculated for finding the good forward route path.

Table 5: QRANK FITNESS ANALYSIS

QRank	Fitness Criteria
0	Latency
	Link Quality
	Throughput
	Reliability
1	Latency
	Reliability
	Energy Consumption
2	Distance
	Reliability
	Energy Consumption

On the selected multi-hop route the data is transmitted to gateway. Consideration of diverse criteria for different data ensures the required level of QoS without an increase in energy consumption.

5.6. *Weighted Sleep Scheduling*

The weighted duty cycle procedure is established in order to reduce resource wastage and information loss in LoRa IoT networks by the end nodes that are not always needed and cause an unnecessary energy consumption from which results void holes by taking into consideration different nodes factors, the decision on the end nodes status can be taken effectively. For accurate timeslots selection, buffer status, energy status and event status were used. We focus on minimizing the node level energy consumption without degradation of the QoS level. Thus, we present dynamic sleep scheduling procedure for IoT nodes. Each node makes decision on sleep time slot by using Multi-Weighted Sum Model (MWSM) that considers multiple criteria such as buffer status β_δ, energy status ε_δ and event status εt_δ . Fig. 5 and 6 represents the sleeping time slot conditions prediction and MWSM model for determining the optimum set of timeslots for nodes based on the historical status.

With the use of β_δ, ε_δ, and εt_δ and sleep time slot φ_Γ determined and few conditions are follows,

If (β_δ ==Short) && (ε_δ==Short) && (εt_δ == Short)

$\varphi_{\hat{\Gamma}}$ = **High**

Else if (β_δ ==Medium) && (ε_δ==Medium) &&

(εt_δ == Medium)

$\varphi_{\hat{\Gamma}}$ = **Medium**

Else if (β_δ ==Large) && (ε_δ==Large) &&

(εt_δ == Large)

$\varphi_{\hat{\Gamma}}$ = **Low**

Figure 5: Sleeping time slot conditions prediction

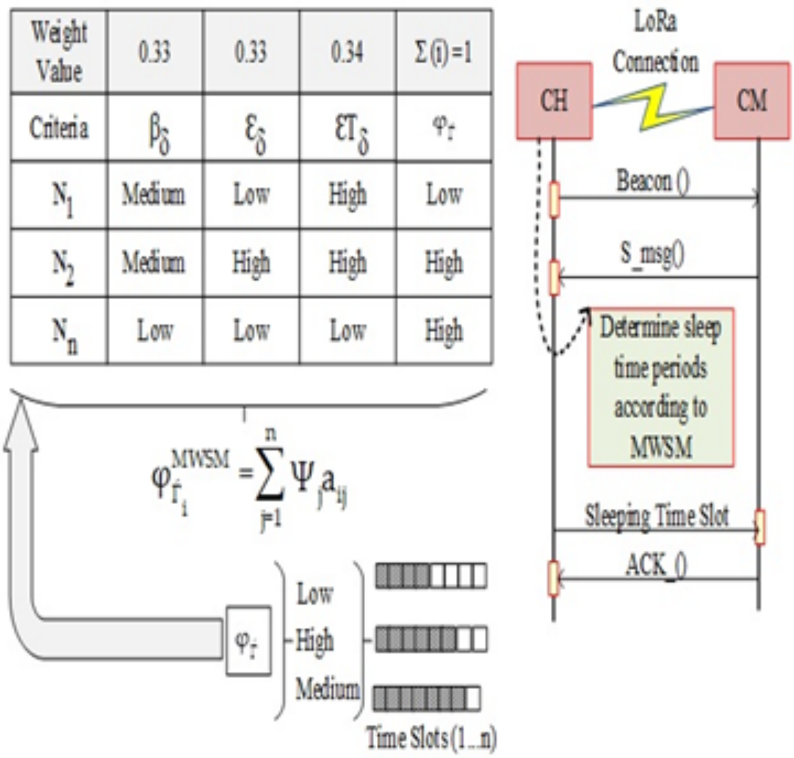

Figure 6: MWSM model

However, energy consumption of IoT N_i is the tradeoff to the quality of sensing. When the sleep scheduling is highly dependent on energy consumption reduction, then the risk of important (emergency) events missing increases gradually.

Mainly each HN in the node aggregates the data and forward it to the HM through an optimal selected route, in case the energy dissipation are detected during the process the HM then takes optimal decision on the void energy dissipation. All IoT devices considered in this paper are assumed to be heterogeneous, i.e., pressure, temperature, humidity and other environment or any other specific information is sensed by IoT devices. Therefore, both emergency and non-emergency events are sensed by nodes as represented in Fig.7 as sleep scheduling. Lack of sleep scheduling is the best possible way to introduce information loss and energy wastage. As a result, timeslots are assigned according to the task sensing, transmission and reception. In HN, the overall sensed time of HM τ_{sensed} sensed is defined and also it is divided into the number of timeslots as τ_{ϑ} second / minutes). The total number of time slot is defined by

$$\eta_{\delta} = \frac{\tau_{sensed}}{\tau_{\vartheta}} \tag{25}$$

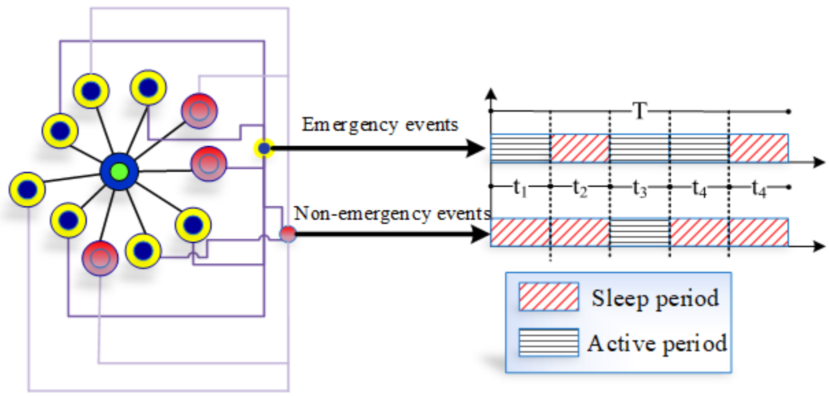

Figure 7: Sleep scheduling

The mathematical expression for sleeping time slot prediction by MWSM is as follows: three criteria such as β_δ, ε_δ, and εt_δ must be lower to show the better φ_Γ. Then, relative weight value is computed for all criterion and it is represented as Ψ_j. The score for MWSM is computed by follows

$$\varphi_{\Gamma i}^{MWSM} = \sum_{j=1}^{n} \Psi_j a_{i,j} \; for \; i = 1, 2 \ldots n \tag{26}$$

where $a_{i,j}$ is the number of end nodes from 1 to n. The consideration of multiple criteria prevents the energy dissipation and also prevents all nodes from entering into sleep state. The HN sets timeslot i for HM_i by follows:

$$HM_i^\varepsilon = \begin{Bmatrix} 1 & if \; \varepsilon t_\delta(j) > 0 \\ 0 & if \; \varepsilon t_\delta(j) = 0 \end{Bmatrix} \tag{27}$$

In Eqns.(27), $\varepsilon t_\delta(j) > 0$, represents the emergency events as sensed by HM_i^ε, and $\varepsilon t_\delta(j) = 0$, represents emergency events are not sensed by the node.

Algorithm 1 Pseudocode for MWSM

```
Input:
    τ_sensed = τ(τ_ϑ1)...τ(τ_ϑn)
Output:
    η_δ
Start:
    Initialize clusters,
        C_i = C_1, C_2, C_3, ..., C_n
        For each C_i
            For all N_i ∈ C_i
            Find φ_Γ
            Sort all N
            Find threshold
    If(φ_Γ < threshold)
         Allocate N_{i→2t} Allocate N_{i→t}
```

6. EXPERIMENTAL EVALUATION

This section describes the experiments evaluation of the MQ-LoRa solution. The key objective of performed experiments is to investigate the effectiveness of MQ-LoRa. There are three sub-sections that are presented in this study, include simulation setup, performance metrics and comparative study.

6.1. Simulation Setup

In order to show the efficiency of the proposed MQ-LoRa model over the previous methods, the NS3.26 simulator is used. LoRa can support multiple gateways with wide-range of coverage. With the utilization of multiple gateways, it is easy to obtain the higher packet delivery ratio and lesser energy consumption than the single gateway used. The NS3 module can accurately perform simulation for LoRa. In particular, the LoRaWAN module is used in NS3 and the specialized header files used in the LoRa simulation are given in Fig. 8.

```
/* NS3 Module */
modules_enabled = ['lorawan']
./test.py -s lorawan
-------------------------------------
/* Header Files */
#include "lora-packet-tracker.h"
#include "ns3/log.h"
#include "ns3/simulator.h"
#include "ns3/lorawan-mac-header.h"
#include "ns3/lora-net-device.h"
#include "ns3/lora-tx-current-model.h"
#include "ns3/end-device-lora-phy.h"
```

Figure 8: NS3 module and header files for LoRa

In this network simulation, the total number of LoRa end devices that taken into account is 50. The LoRa gateways are 5, 1 network server and 1 cloud server is deployed in the network for processing applications. Total simulation time is 300 seconds. The simulation network area is $1000 * 1000m^2$. Total simulation parameters and its values are illustrated in Table 6 and Table 7.

Prototype Testing: The proposed MQ-LoRa routing protocol is implemented for smart city application, specifically, air quality monitoring. For that, various IoT devices (sensors) are deployed such as gas sensors, humidity sensors, noise level sensors, amongst others. The key objective of these sensor nodes is to senses the environment and to transmit the sensed data to sink node. Further the sink node sends the aggregated data to the expert system via the Internet as illustrated in Fig. 9. Finally the expert system analyzes the received data and transmits the decision to the end user. In the application of smart city, it is necessary to deploy a large number of IoT devices since the sensing area will be large, e.g., a city. Hence, LoRa communication technology is used to cover this smart city. Likewise, the generated data is huge in volume and velocity. Transmitting this data from a huge number of IoT devices drains the energy of all nodes and minimize the network lifetime. Interruption in communication due to the node dead is not acceptable for smart city application as it reduces the quality of data. Thus, the smart city application is well suited for testing the proposed energy conservation scheme. The sensing attributes used in the air quality application are listed in Table 8 and 9.

All sensed air quality monitoring attributes and the nature of sensor event type is described in Table 8. When the event status of any of sensor nodes exceeds the set threshold values, then it is considered to be emergency state [46, 47]. Then that type of sensed packets is forwarded to the gateway through the HNs. As per the international standard, sensor readings are classified into two classes as emergency and non-emergency readings. For the sensed information, spreading factors are computed for the number of sent bytes. The network simulation implemented by NS3 is illustrated in Fig. 9. In this figure, the LoRa node is denoted as a red circle, the LoRa gateway is denoted by yellow triangle and the communication link is represented in a green line.

Table 6: SIMULATION PARAMETERS

Parameters	Value	
Network Settings		
Environment Size	1000×1000m	
# of IoTDevices	50	
# of Gateways	5	
Network Server	1	
Cloud Server	1	
Node Settings		
Initial Energy of nodes	50J	
Propagation Model	LoRa Log Normal Shadowing Model	
Number of Retransmissions	7 (Max)	
[HTML]F00 Transmission Power	14 dBm	
Packet Length	51 bytes	
Maximum Distance to Gateway	1000m	
Distance between Gateways	1000m	
Data Rate	88Mbps (Max)	
Number of Slots	16	
Slot Duration	10 s	
LoRa Settings		
	Range	Sensitivity (dBm)
	7	-130
LoRa Gateway	8	-132.5
Spreading Factor	9	-135
	10	-137
	11	-140
	12	-142
Voltage	3.3v	
Frequency band	868mhz	
Duty cycle	1-5%	
Code Rate	4/5	
Payload Length	10 bytes	
Bandwidth	125khz	
# of channels	3	
Time slot technique	CSMA10	
Number of Rounds	1000	
Simulation Time	300s	
Number of Clusters	8-10	
Average Inter Packet Interval	120 per second	
Interface Queue Type	Priority Queue	
Resync Period	30 minutes	
Processing Delay	Less than 20ms	
Communication hops	Min – 20, Max – 50, Average - 25	

Table 7: ALGORITHM PARAMETERS

Algorithm Parameters	
SAC	
No. of hidden layers	5
No. of samples	512
Updating of target interval	1
Learning rate	4×10^{-5}
Activation function	ReLU
Discount factor	99×10^{-1}
Smoothing co-eff	0.008
Reply buffer size	10^8
Mayfly	
Population size	100
Attraction co-eff	1.2
Visibility co-eff	1
Cross over rate	0.90
Random flight	0.7
Nuptial dance	0.5

Table 8: AIR QUALITY SENSING ATTRIBUTES

Sensing Attributes	**Injuriousness Monitoring**	**Output Unit**	**Description**
Air Quality	SO2, NO2, Co, Pb, etc	0.0148 ppm-3.24 ppm	It sense toxicity level of air
Temperature	0 C	0 C - 35 C	It sense high temperature level of smart city
Noise	Occupational, peak noise	75-140dp	It sense noise level of smart city

Table 9: AIR QUALITY SENSING ATTRIBUTES

Air pollutant	**Emergency Readings**	**Non-Emergency Readings**	**delta**	**Sent Bytes**
Sulphar Dioxide SO_2	0.00709 ppm	0.0177 ppm	12	50
	0.0284 ppm	0.0284 ppm	12	50
Nitrogen Dioxide NO_2	0.0197 ppm	0.0148 ppm	9	115
	0.0395 ppm	0.0395 ppm	7	212
Particulate Matter PM_10	60 (g/m3)	60 (g/m3)	12	49
	100 (g/m3)	100 (g/m3)	12	46
Ozone O_2	0.0473 ppm	0.0473 ppm	12	51
	0.0852 ppm	0.0852 ppm	8	210
Lead P_b	0.5 g/m3	0.5 g/m3	12	50
	1 g/m3	1 g/m3	9	88
Carbon Monoxide CO	1.62 ppm	1.62 ppm	12	50
	3.24 ppm	3.24 ppm	12	50
Ammonia NH_3	0.133 ppm	0.133 ppm	9	58
	0.533 ppm	0.533 ppm	12	50

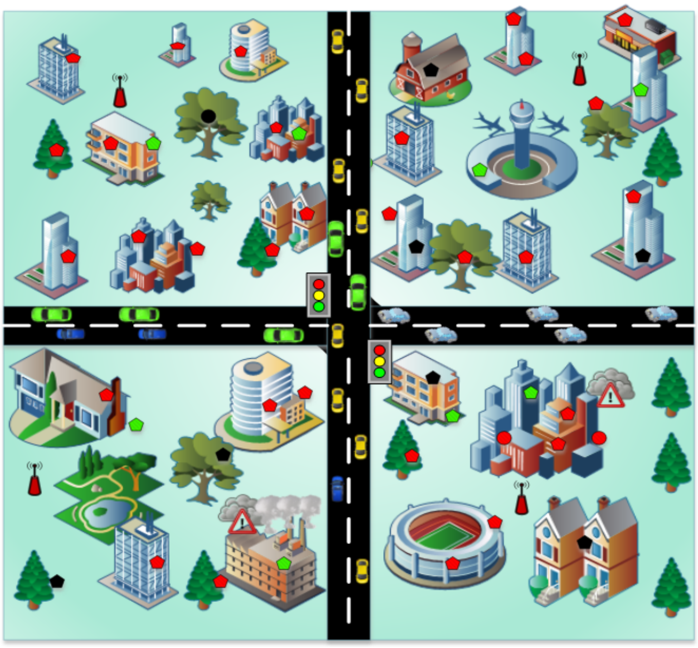

Figure 9: Application scenario of smart city

6.2. *Performance Metrics*

This section describes the performance metrics taken into account for examining the simulation of MQ-LoRa.
a) Packet Reception Rate Packet reception rate describes that the proportion of packets being received successfully p(su) over the time. However, p(su) is influenced by the SINR, RSS and channel relationship network elements.

$$p(su) = SINR, C, RSS \tag{28}$$

b) Energy consumption. According to LoRa communication in NS3, we define the energy consumption metric as follows,

$$EC = \frac{T.exp(2(NTL)SF}{PS} \tag{29}$$

where T is energy consumption for first transmission attempt, 2NTLSF is the normalized traffic load per SF and PS is the payload size.

c) Delay
Delay is computed by the amount of time that requires to send a packet from source to the destination. It encompasses processing, waiting and transmission delays. Delay is calculated as follows

$$Delay = (Ar)_t - (Gr)_t \tag{30}$$

where $(Ar)_t$ is the packet arrival time and $(Gr)_t$ is the packet generation time.
(d) Packet Rejection Rate
Packet rejection rate is calculated as the number of failures in packet transmission over a time. A packet probability failure rate is 1-p(su) and after the certain number of transmissions, i.e., l, the packet rejection rate P_r computed as follows,

$$P_r = [1 - p(su)]^l \tag{31}$$

(e) Throughput
Throughput is computed for the number of devices N_i in which every t_i seconds, packets are sensed and transmitted

through a specified channel for t_i^p. In this time, network traffic is computed by,

$$G = \sum_{i=1}^{N} \frac{t_i^p}{\tau_i} \tag{32}$$

For network traffic G, throughput T is then calculated as,

$$T = G \times \rho_{success\ rate} \tag{33}$$

where $\rho_{success\ rate}$ is the successful packet transmission ratio which is computed from the number of transmitted packets to the number of received packets.

6.3. Comparative Study

In this section, we present the comparative study for the proposed MQ-LoRa to the existing methods such as RT-LoRa, Multi-Hop and LoRa+. The simulation environment implemented by NS3 is illustrated in Fig. 10. We perform this comparative study based on the effectiveness of the existing methods in terms of packet reception rate, energy consumption, delay, packet rejection ratio and throughput.

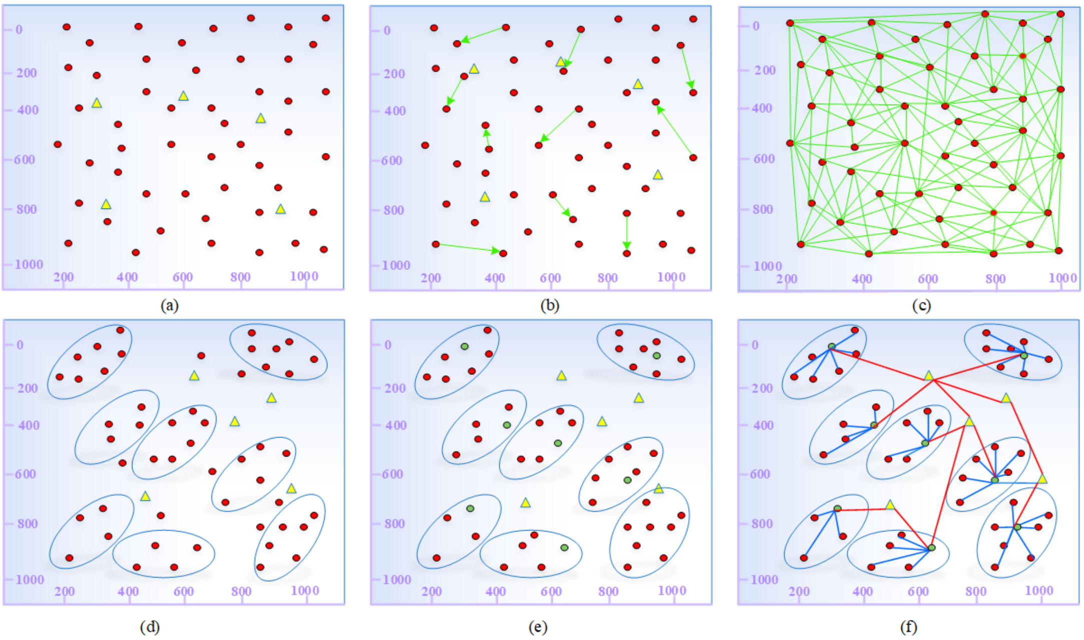

Figure 10: Simulation environment (a). Nodes deployment, (b). Control message transmission, (c). Node communication, (d). Cluster formation, (e). HN Election and (f). Cluster-tree topology

6.3.1. Effectiveness of Packet Reception Rate

Fig. 11 indicates the packet reception rate for the proposed MQ-LoRa and the previous methods as RT-LoRa, Multi-Hop and LoRa+. It is observed that the packet reception rate of RT-LoRa, Multi-Hop and LoRa+ are 30%, 40%, and 40% lesser than the proposed MQ-LoRa, respectively. This is due to the efficient routing of packets between HNs which reduces packet losses or retransmission. Further, routing is made by the optimum transmission policy enforcement in which the number of packets transmitted increases and the availability of next hop for data transmission also increases, and hence the packet reception rate increases as the number of nodes increases.

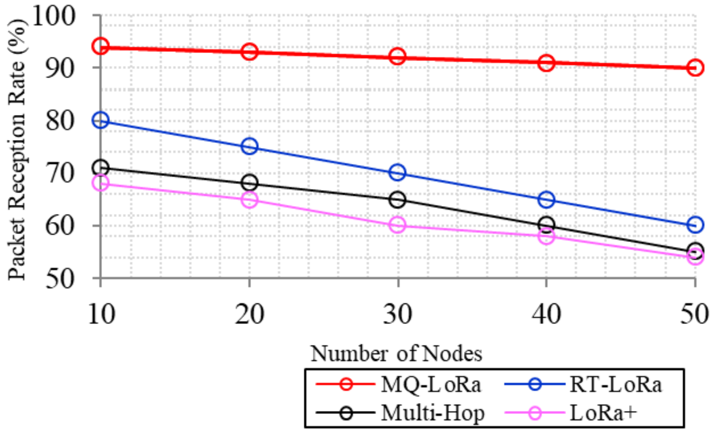

Figure 11: Number of Nodes vs. Packet Reception Rate

Fig 12 represents the packet reception rate with respect to the number of gateways. It can be observed that the single gateway does not ensure the high packet reception rate, which cannot support simultaneous packet reception. Based on the number of IoT devices, optimum set of gateways must be deployed to reduce the losses in data transmission. Due to the accurate HN selection, multi-hop routing and QRank prediction, in this paper MQ-LoRa has obtained the better packet reception rate in terms of both number of devices and the number of gateways.

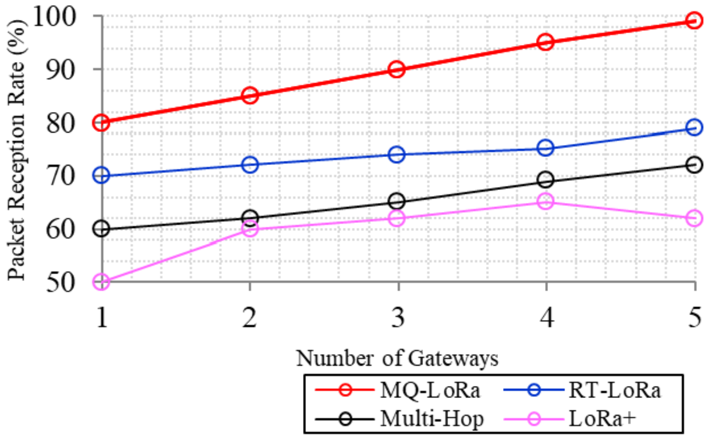

Figure 12: Number of Gateways vs. Packet Reception Rate

6.3.2. Effectiveness of Energy Consumption

Energy consumption is a significant metric in resource constrained environment. It is increasing when the number of nodes increases due to network congestion traffic.

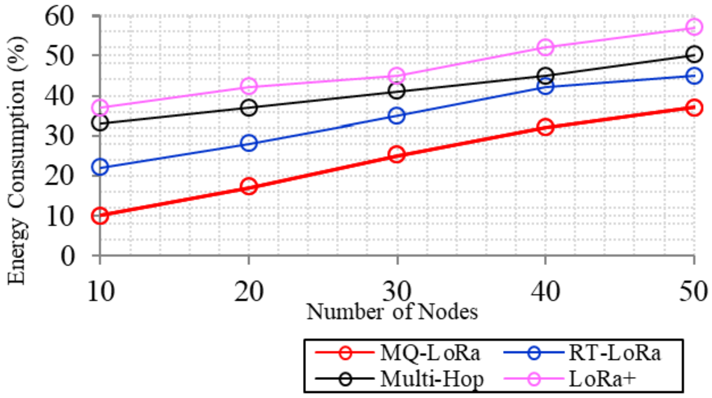

Figure 13: Number of Nodes vs. Energy Consumption

Fig. 13 shows the result of energy consumption with respect to the number of nodes. It is observed that the evaluation of energy consumption for the proposed MQ-LoRa is better than the RT-LoRa, Multi-Hop and LoRa+. For instance, the energy consumption for the number of nodes at 10 is 32%, 38%, and 52% for RT-LoRa, Multi-Hop and LoRa+ respectively. In MQ-LoRa, the IoTdevices consume less energy as compared to RT-LoRa, Multi-Hop and LoRa+. It is mainly due to the effective HN selection and hybrid topology construction. Additionally, the MQ-LoRa considers metrics such as residual energy, event status and spreading factor for route selection. It balances the network traffic through HN selection. Thus, the overall network lifetime is prolonged even when sending large number of packets. It also solves the hotspot issue in a certain extent. Fig. 14 shows the performance analysis of the energy consumption with respect to the number of gateways. In terms of gateways, the energy consumption rate is reduced. The availability of gateways in distributed environment reduce the energy consumption rate of IoT devices since communication delay is reduced.

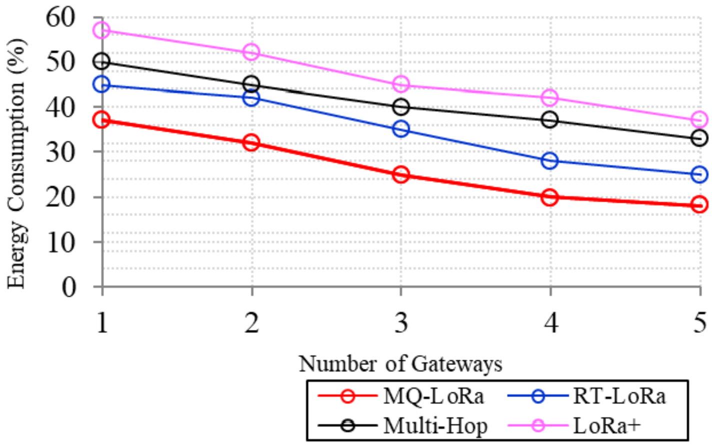

Figure 14: Number of Gateways vs. Energy Consumption

6.3.3. Effectiveness of Delay

Fig. 15 represents the delay for varying number of nodes. It can be observed that the delay by MQ-LoRa is acceptable due to the propagation, waiting and packet transmission states. In particular, the delay of RT-LoRa, Multi-Hop and LoRa++ are 6.5s, 13s and 14s respectively. It is owing to the formation of clusters in IoTdevices and it applies the membrane inspired clustering for effective cluster formation and HN selection. In addition, optimum transmission policy is enforced by the fast DRL which result in lesser delay.

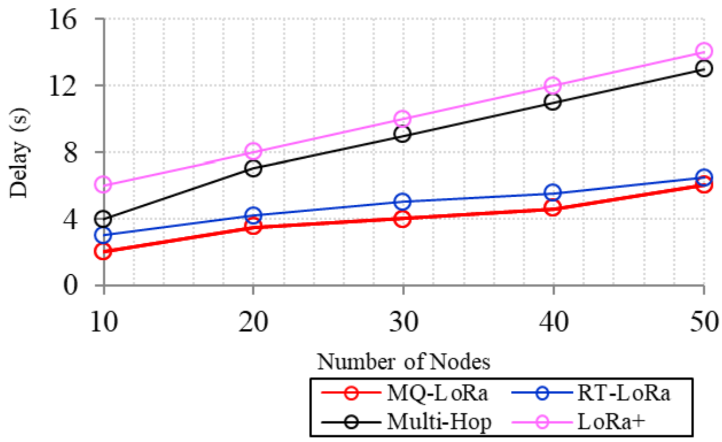

Figure 15: Number of Nodes vs. Delay

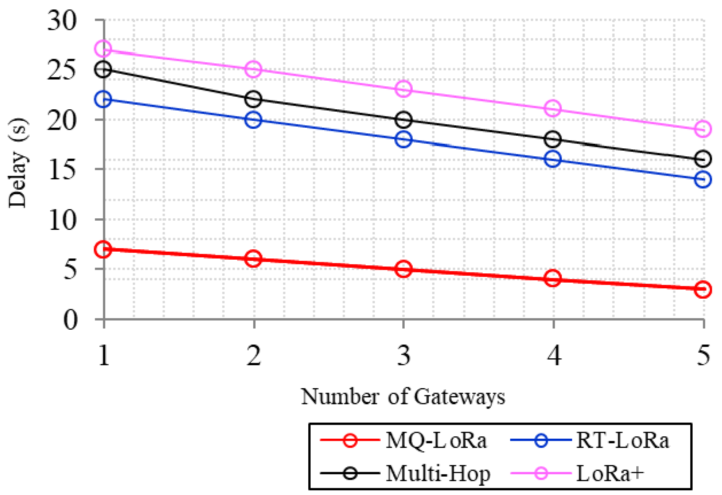

Figure 16: Number of Gateways vs. Delay

The performance of delay with respect to the number of gateways is plotted in Fig.16 As a result of multiple gateways, MQ-LoRa has obtained significant reduction in packet routing delay.

6.3.4. Effectiveness of Packet Rejection Rate

Fig. 17 depicts the packet rejection rate with respect to the number of nodes. The packet rejection rate shows that rejected packets rate in terms of percentage. It is computed by the total number of packets forwarded by the source node.

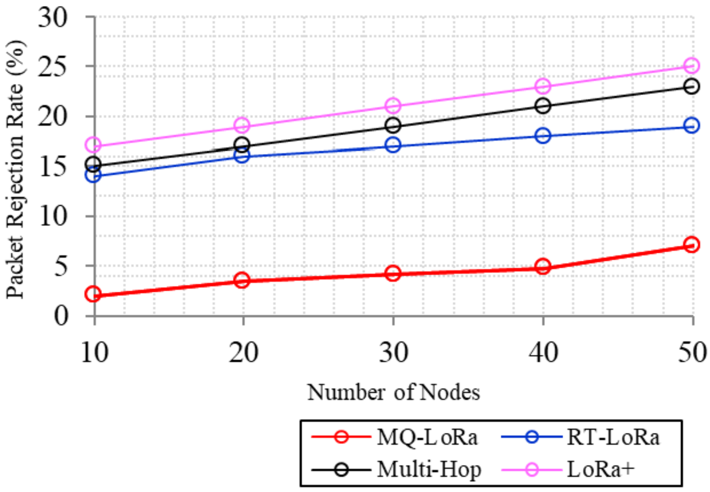

Figure 17: Number of Nodes vs. Packet Rejection Rate

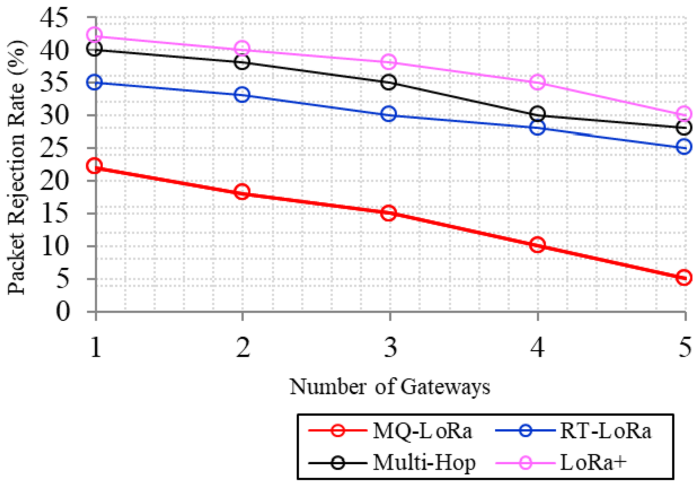

Figure 18: Number of Gateways vs. Packet Rejection Rate

This metric measures the packets forwarding reliability and the effectiveness of the hybrid network topology deployed in MQ-LoRa model. The performance of packet rejection rate increases compared LoRA+, Multi-Hop and RT-LoRa by 25%, 22%, and 17% respectively. However, the proposed MQ-LoRa has achieved 7% for the number of devices of 1000. Similarly, Fig. 18 illustrates the performance of packet rejection ration with respect to the number of gateways. The proposed MQ-LoRa results in no route breakages in data transmission. From the analysis, it reveals that when number of nodes increases, then the probability of rejection also increases due to the lack of optimum route establishment by efficient fitness criteria. Further, LoRa communication parameters must be optimized. These reasons impact the performance high packet rejection rate.

6.3.5. Effectiveness of Throughput

The effectiveness of throughput with respect to the number of nodes and gateways are represented in Fig. 19 and Fig. 20, respectively. The result obtained in network throughput exhibits an increase in MQ-LoRa's throughput which is owing to the lightweight use of algorithms and fewer computations are required in this modified LoRa protocol. Currently, emergency packets are affected due to the QoS issues in the disaster cases. For that, QoS QRank field is additionally included in the LoRa packet header frame structure and hence the throughput is improved and the overall

QoS is enhanced for emergency and non-emergency packets. When the network congestion level is high, then the number of packet transmission is lesser, which leads to minimum throughput.

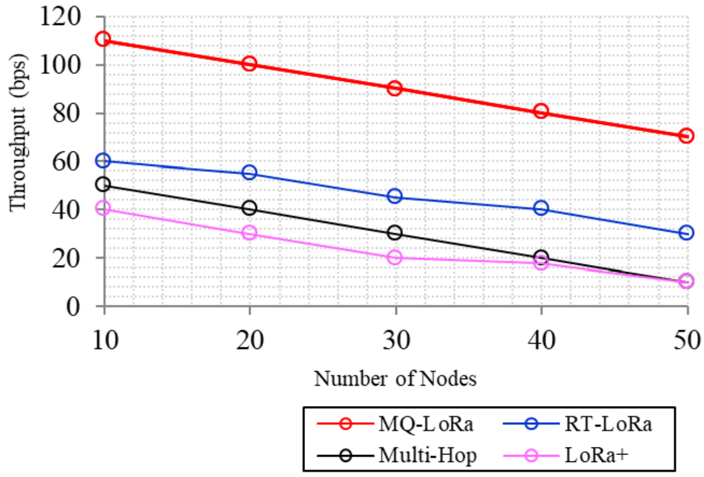

Figure 19: Number of Nodes vs. Throughput

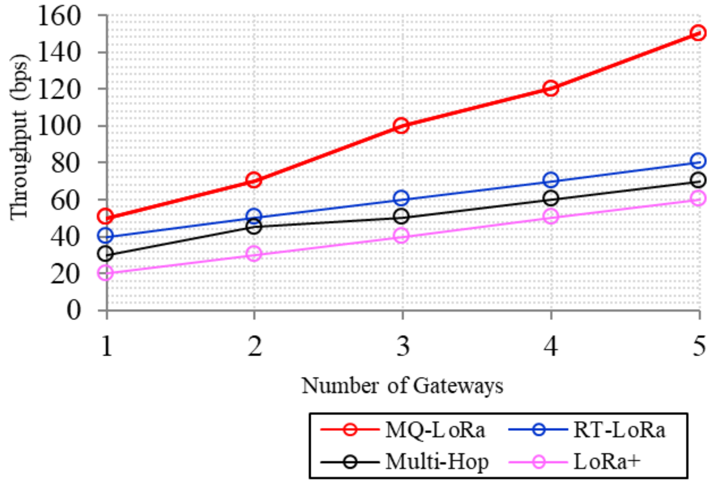

Figure 20: Number of Gateways vs. Throughput

6.3.6. Discussion Section

From the above-mentioned simulation results, it is clear that the proposed MQ-LoRa has outperformed previous research. Computational Complexity Analysis: Our literature review shows that existing research efforts that attempt to solve LoRa's energy consumption and QoS problems has been partially successful. They also suffer from high computational complexity compared to MQ-LoRa. In the following, we provide analysis of the computational complexity of the MQ-LoRa,

$$(\Delta t) + O(N) + O(N) + O(\Delta + [NM] \tag{34}$$

where $O(\Delta t)$ is the time duration for topology construction, cluster formation and selection, O(N) is the QoS ranking, O(N) is the transmission policy enforcement, and $O(\Delta(N + M))$ is the multi-hop routing and sleep scheduling. Reliability Analysis: MQ-LoRa addresses network reliability issues through the selection of optimal set of transmission policy parameters through the fast DRL. According to the optimum set of parameters selection, more than

100000 packets are transmitted in 1 hour of network lifetime. The performance of reliability is depicted in Fig. 21. It is relatively higher than the previous methods such as LoRa+, RT-LoRa, and Multi-Hop routing protocol.

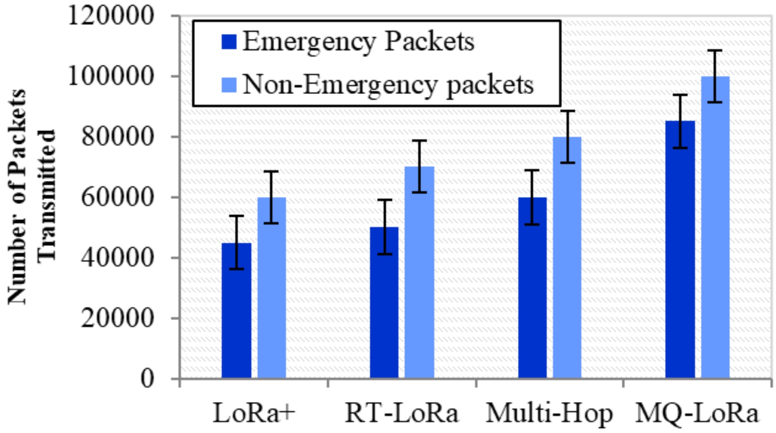

Figure 21: Reliability analysis

7. CONCLUSION

7.1. Conclusion

In this paper, a multi-hop QoS aware LoRa routing protocol is presented in which optimum transmission policy enforcement is advocated to improve the QoS in LoRa communication. To meet the QoS requirements for any IoT application, this paper adopts various techniques. Energy consumption is reduced by forming clusters of end nodes. Various node characteristics are considered to create stable and efficient clusters and an HN is selected in each cluster. Further, end-to-end communication delay is minimized by conducting data transmission via HNs to the gateway. Then, data QoS ranking is predicted by the entropy function which predicts the packet rank to classify as emergency or non-emergency. An optimal set of LoRa parameters are obtained in the transmission policy enforcement step. In this step, a fast DRL algorithm is used for learning the environment and parameter values are fixed. Finally, multi-hop routing is predicted by parallel optimization algorithms, i.e., Mayfly and shuffled shepherd optimization. These algorithms find the available routes in a parallel mode and choose the fitness criteria met route for data transmission. Further, energy consumption is reduced by implementing a sleep scheduling mechanism. In this paper, a weighted sum model is presented to analyze the optimum set of timeslots for giving the node as sleep state. Finally, the performance is analyzed for packet reception rate, energy consumption, delay, packet rejection rate and throughput. These metrics are compared with the existing methods such as RT-LoRa, Multi-Hop and LoRa+.

7.2. Future Work

Further research needs to be taken to investigate various aspects of LoRa communication including: (1) LoRa based end devices are vulnerable to jamming, replay, beacon synchronization and man-in-the-middle attack. (2) Dynamic movable IoT devices are considered to investigate the mobility problem. (3) Furthermore, an optimal placement concept is used for static gateways that always depend on the application and QoS constraints by the LoRa devices whereas mobile gateways are utilized in network for improving the effectiveness of data collection and aggregation.

8. ACKNOWLEDGEMENT

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